Developing a Customer Churn Prediction Model for SyriaTel Telecommunications Company

In [1]:
```
#import libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import LabelEncoder, MinMaxScaler
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import MinMaxScaler
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import precision_score, accuracy_score, f1_score, recall_score, roc_auc_score, roc_curve, auc, confusi
from sklearn.tree import DecisionTreeClassifier, plot_tree
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier
from imblearn.over_sampling import SMOTE
```

In [2]:
```
# Read the CSV file into a DataFrame
df=pd.read_csv("bigml_59c28831336c6604c800002a.csv")

# Displaying the first 10 rows
df.head(10)
```

Out[2]:

	state	account length	area code	phone number	international plan	voice mail plan	number vmail messages	total day minutes	total day calls	total day charge	...	total eve calls	total eve charge	total night minutes	total night calls	total night charge	total intl minutes	total intl calls	tc cha
0	KS	128	415	382-4657	no	yes	25	265.1	110	45.07	...	99	16.78	244.7	91	11.01	10.0	3	2
1	OH	107	415	371-7191	no	yes	26	161.6	123	27.47	...	103	16.62	254.4	103	11.45	13.7	3	3
2	NJ	137	415	358-1921	no	no	0	243.4	114	41.38	...	110	10.30	162.6	104	7.32	12.2	5	3
3	OH	84	408	375-9999	yes	no	0	299.4	71	50.90	...	88	5.26	196.9	89	8.86	6.6	7	1
4	OK	75	415	330-6626	yes	no	0	166.7	113	28.34	...	122	12.61	186.9	121	8.41	10.1	3	2
5	AL	118	510	391-8027	yes	no	0	223.4	98	37.98	...	101	18.75	203.9	118	9.18	6.3	6	1
6	MA	121	510	355-9993	no	yes	24	218.2	88	37.09	...	108	29.62	212.6	118	9.57	7.5	7	2
7	MO	147	415	329-9001	yes	no	0	157.0	79	26.69	...	94	8.76	211.8	96	9.53	7.1	6	1
8	LA	117	408	335-4719	no	no	0	184.5	97	31.37	...	80	29.89	215.8	90	9.71	8.7	4	2
9	WV	141	415	330-8173	yes	yes	37	258.6	84	43.96	...	111	18.87	326.4	97	14.69	11.2	5	3

10 rows × 21 columns

In [3]:
```
# Displaying columns of our dataframe
df.columns
```

Out[3]:
```
Index(['state', 'account length', 'area code', 'phone number',
       'international plan', 'voice mail plan', 'number vmail messages',
       'total day minutes', 'total day calls', 'total day charge',
       'total eve minutes', 'total eve calls', 'total eve charge',
       'total night minutes', 'total night calls', 'total night charge',
       'total intl minutes', 'total intl calls', 'total intl charge',
       'customer service calls', 'churn'],
      dtype='object')
```

In [4]:
```
# Displaying the rows and columns within our dataframe
df.shape
```

Out[4]:
```
(3333, 21)
```

Data Cleaning

In [5]:
```python
# Retrieve information on columns, data types, non_null count of the data
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3333 entries, 0 to 3332
Data columns (total 21 columns):
 #   Column                  Non-Null Count  Dtype  
---  ------                  --------------  -----  
 0   state                   3333 non-null   object 
 1   account length          3333 non-null   int64  
 2   area code               3333 non-null   int64  
 3   phone number            3333 non-null   object 
 4   international plan      3333 non-null   object 
 5   voice mail plan         3333 non-null   object 
 6   number vmail messages   3333 non-null   int64  
 7   total day minutes       3333 non-null   float64
 8   total day calls         3333 non-null   int64  
 9   total day charge        3333 non-null   float64
 10  total eve minutes       3333 non-null   float64
 11  total eve calls         3333 non-null   int64  
 12  total eve charge        3333 non-null   float64
 13  total night minutes     3333 non-null   float64
 14  total night calls       3333 non-null   int64  
 15  total night charge      3333 non-null   float64
 16  total intl minutes      3333 non-null   float64
 17  total intl calls        3333 non-null   int64  
 18  total intl charge       3333 non-null   float64
 19  customer service calls  3333 non-null   int64  
 20  churn                   3333 non-null   bool   
dtypes: bool(1), float64(8), int64(8), object(4)
memory usage: 524.2+ KB
```

There are no null values

In [6]:
```python
# Check if there any duplicated rows
df.duplicated().sum()
```

Out[6]: 0

There are no duplicates

In [7]:
```python
# Get the count of unique values in the "churn" column
df["churn"].value_counts()
```

Out[7]:
```
False    2850
True      483
Name: churn, dtype: int64
```

In [8]:
```python
# Iterating over each column to print unique values in each column.
columns=df.columns
for col in columns:
    print(col, df[col].unique())
```

```
  4.5  6.5 15.6  5.9 18.9  7.6  5.   7.  14.  18.  16.  14.8  3.7  2.
  4.8 15.3  6.  13.6 17.2 17.5  5.6 18.2  3.6 16.5  4.6  5.1  4.1 16.3
 14.9 16.4 16.7  1.3 15.2 15.1 15.9  5.5 16.1  4.  16.9  5.2  4.2 15.7
 17.   3.9  3.8  2.2 17.1  4.9 17.9 17.3 18.4 17.8  4.3  2.9  3.1  3.3
  2.6  3.4  1.1 18.3 16.6  2.1  2.4  2.5]
total intl calls [ 3  5  7  6  4  2  9 19  1 10 15  8 11  0 12 13 18 14 16 20 17]
total intl charge [2.7  3.7  3.29 1.78 2.73 1.7  2.03 1.92 2.35 3.02 3.43 2.46 3.32 3.54
 1.46 3.73 2.19 3.51 2.86 1.54 2.57 2.08 2.78 4.19 3.97 3.   3.83 3.4
 3.19 2.24 3.92 2.84 2.54 3.94 2.48 0.95 2.3  3.56 2.   2.38 2.97 2.11
 1.84 3.08 2.51 2.62 2.75 2.16 1.57 3.27 3.24 3.13 2.21 1.67 1.97 1.65
 3.16 4.05 2.65 3.35 2.32 2.94 3.75 2.4  2.13 1.43 1.19 3.38 3.05 2.43
 2.59 3.59 5.4  1.94 1.73 3.81 3.86 1.86 3.11 4.27 3.46 4.37 0.   3.21
 2.67 2.27 2.92 3.62 2.89 4.75 1.27 0.73 3.65 3.48 3.89 2.81 1.81 4.16
 1.22 1.76 4.21 1.59 5.1  2.05 1.35 1.89 3.78 4.86 4.32 4.   1.   0.54
 1.3  4.13 1.62 3.67 4.64 4.73 1.51 4.91 0.97 4.46 1.24 1.38 1.11 4.4
 4.02 4.43 4.51 0.35 4.1  4.08 4.29 1.49 4.35 1.08 4.56 1.4  1.13 4.24
 4.59 1.05 1.03 0.59 4.62 1.32 4.83 4.67 4.97 4.81 1.16 0.78 0.84 0.89
 0.7  0.92 0.3  4.94 4.48 0.57 0.65 0.68]
customer service calls [1 0 2 3 4 5 7 9 6 8]
churn [False  True]
```

In [9]:
```
# Selecting numerical columns with float data type
numerical_columns=df.select_dtypes(include=["float"])
```

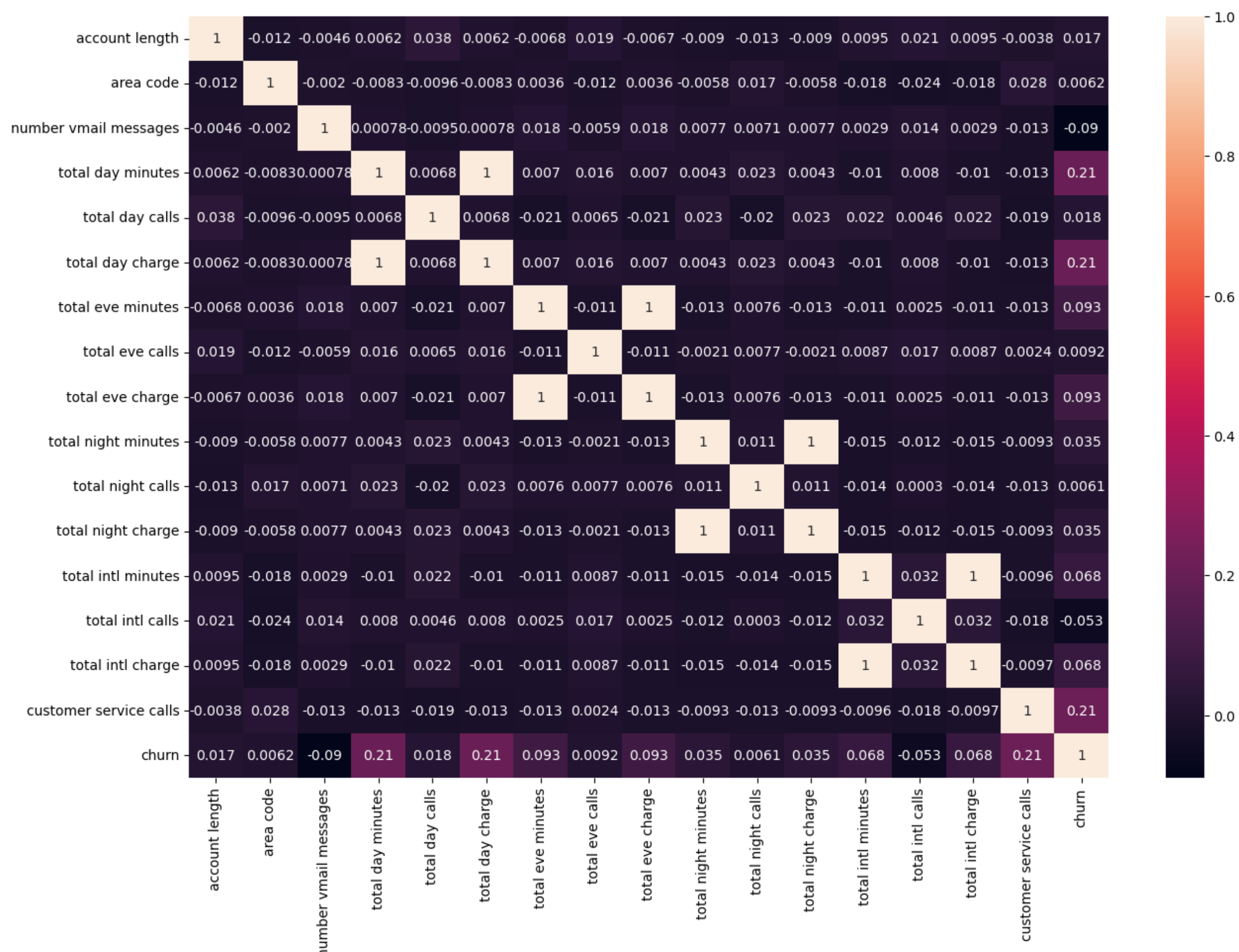
In [10]:
```
# Rounding the values to decimal places for data uniformity
numerical_columns.round(2).head(10)
```

Out[10]:

	total day minutes	total day charge	total eve minutes	total eve charge	total night minutes	total night charge	total intl minutes	total intl charge
0	265.1	45.07	197.4	16.78	244.7	11.01	10.0	2.70
1	161.6	27.47	195.5	16.62	254.4	11.45	13.7	3.70
2	243.4	41.38	121.2	10.30	162.6	7.32	12.2	3.29
3	299.4	50.90	61.9	5.26	196.9	8.86	6.6	1.78
4	166.7	28.34	148.3	12.61	186.9	8.41	10.1	2.73
5	223.4	37.98	220.6	18.75	203.9	9.18	6.3	1.70
6	218.2	37.09	348.5	29.62	212.6	9.57	7.5	2.03
7	157.0	26.69	103.1	8.76	211.8	9.53	7.1	1.92
8	184.5	31.37	351.6	29.89	215.8	9.71	8.7	2.35
9	258.6	43.96	222.0	18.87	326.4	14.69	11.2	3.02

In [11]:
```
corr_matrix=df.corr(numeric_only=True)
plt.figure(figsize=(15,10))
sns.heatmap(data=corr_matrix, annot=True)
```

Out[11]: <Axes: >



In [12]:
```
df.corr(numeric_only=True)['churn']
```

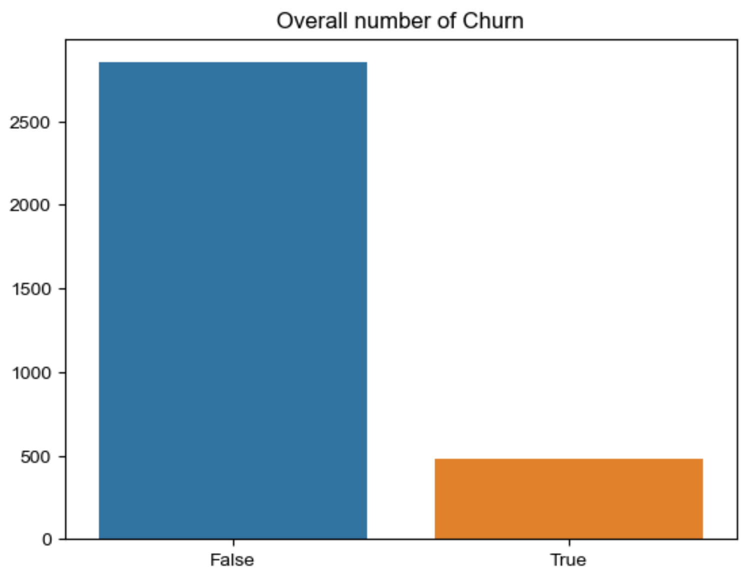
Out[12]:
```
account length            0.016541
area code                 0.006174
number vmail messages    -0.089728
total day minutes         0.205151
total day calls           0.018459
total day charge          0.205151
total eve minutes         0.092796
total eve calls           0.009233
total eve charge          0.092786
total night minutes       0.035493
total night calls         0.006141
total night charge        0.035496
total intl minutes        0.068239
total intl calls         -0.052844
total intl charge         0.068259
customer service calls    0.208750
churn                     1.000000
Name: churn, dtype: float64
```

From the above results these correlation results provide valuable insights into the relationship between different features and churn behavior, either being positive correlated or negative.

From correlations results, it is recommended that future studies be done to explain causation because correlation shows causality and not causation

Data Visualization

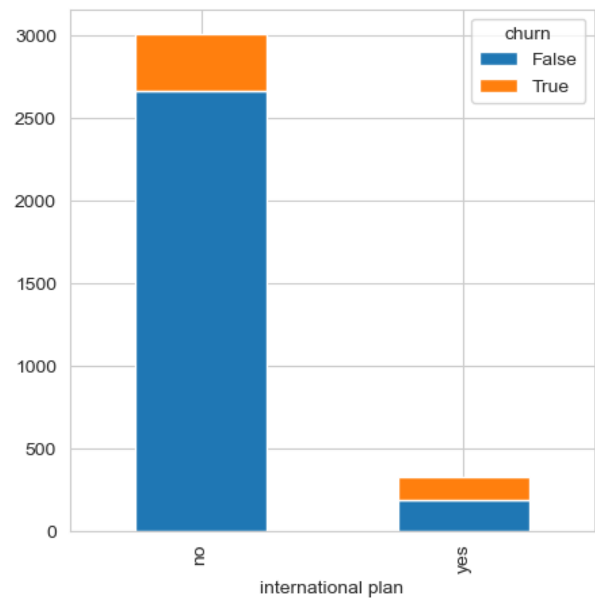
In [13]:
```
# calculating overall churn rate
churn = df['churn'].value_counts()
sns.barplot(x=churn.index, y=churn.values)
plt.title('Overall number of Churn')
sns.set_style('whitegrid')
plt.show()

churn_rate = ((sum(df['churn'] == True)/ len(df['churn'])*100))
print('Overall Churn rate is ', round(churn_rate, 2), '%')
```




```
Overall Churn rate is  14.49 %
```

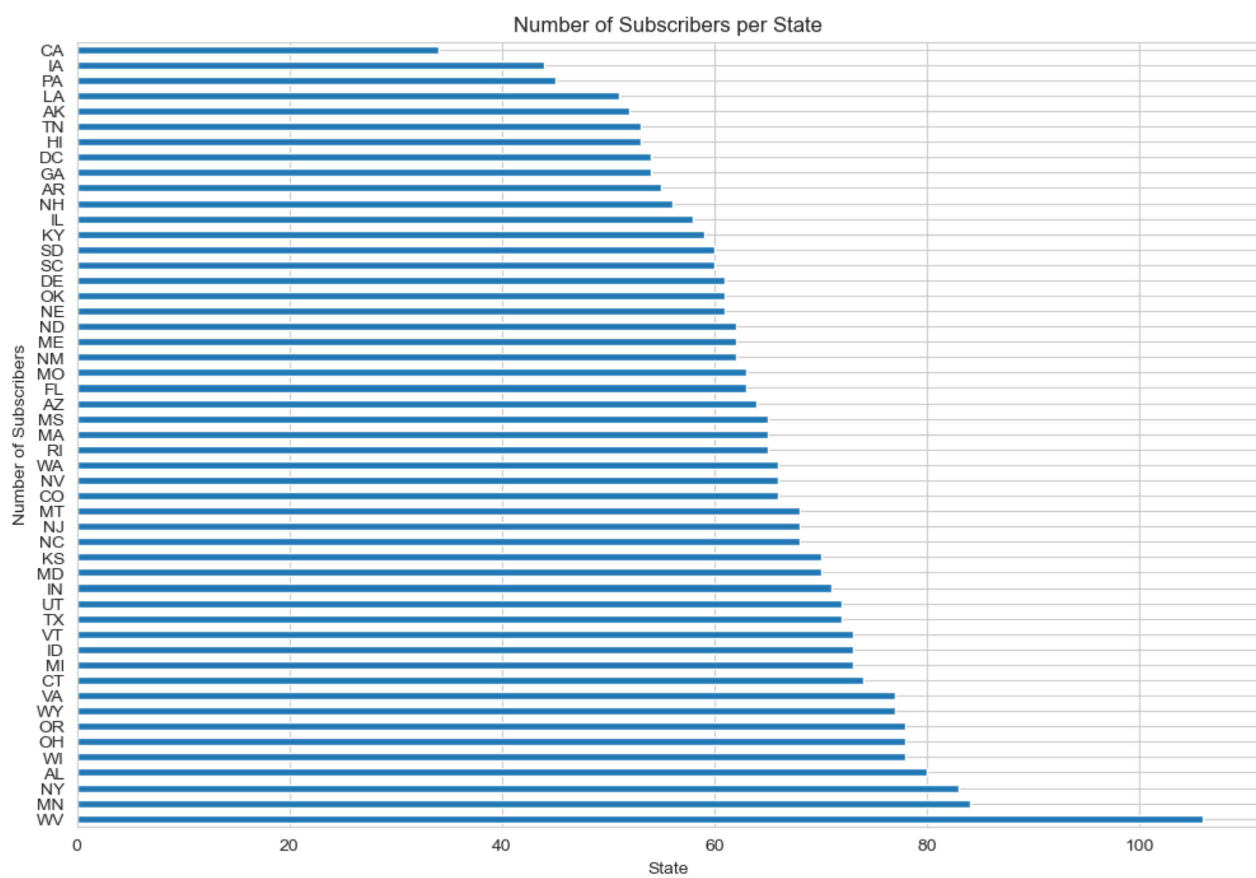
In [14]:
```
#Visualizing the distribution of churned and non-churned customers grouped by their international plan.
df.groupby(["international plan", "churn"]).size().unstack().plot(kind='bar', stacked=True, figsize=(5,5))
```

Out[14]: <Axes: xlabel='international plan'>



From the category international plan, a higher percentage are not subscribed to the plan. From those who are not subscribed, a smaller number churned. Of the international plan subscribers, a smaller section churned.

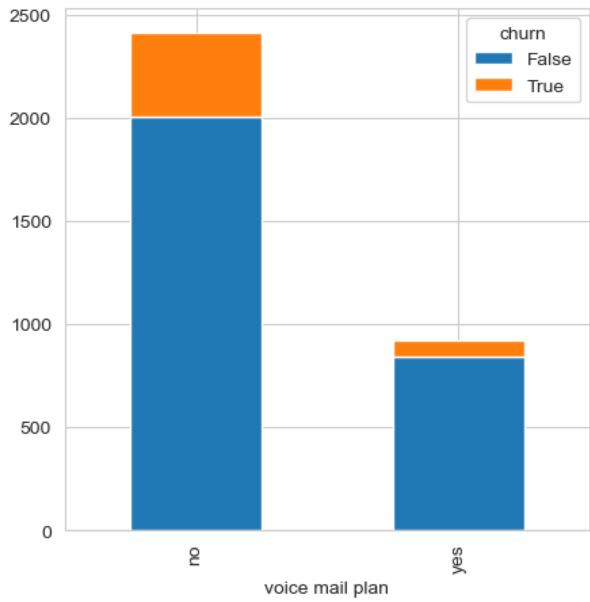
In [15]:
```
# Visualizing number of subscribes per state
plt.figure(figsize=(12, 8))
df['state'].value_counts().plot(kind='barh')
plt.title('Number of Subscribers per State')
plt.xlabel('State')
plt.ylabel('Number of Subscribers')
plt.show()
```



From the above graph most subscribers are based on the WV state.

In [16]:
```python
#Visualizing the distribution of churned and non-churned customers grouped by their voice mail plan subscription.
df.groupby(["voice mail plan", "churn"]).size().unstack().plot(kind='bar', stacked=True, figsize=(5,5))
```

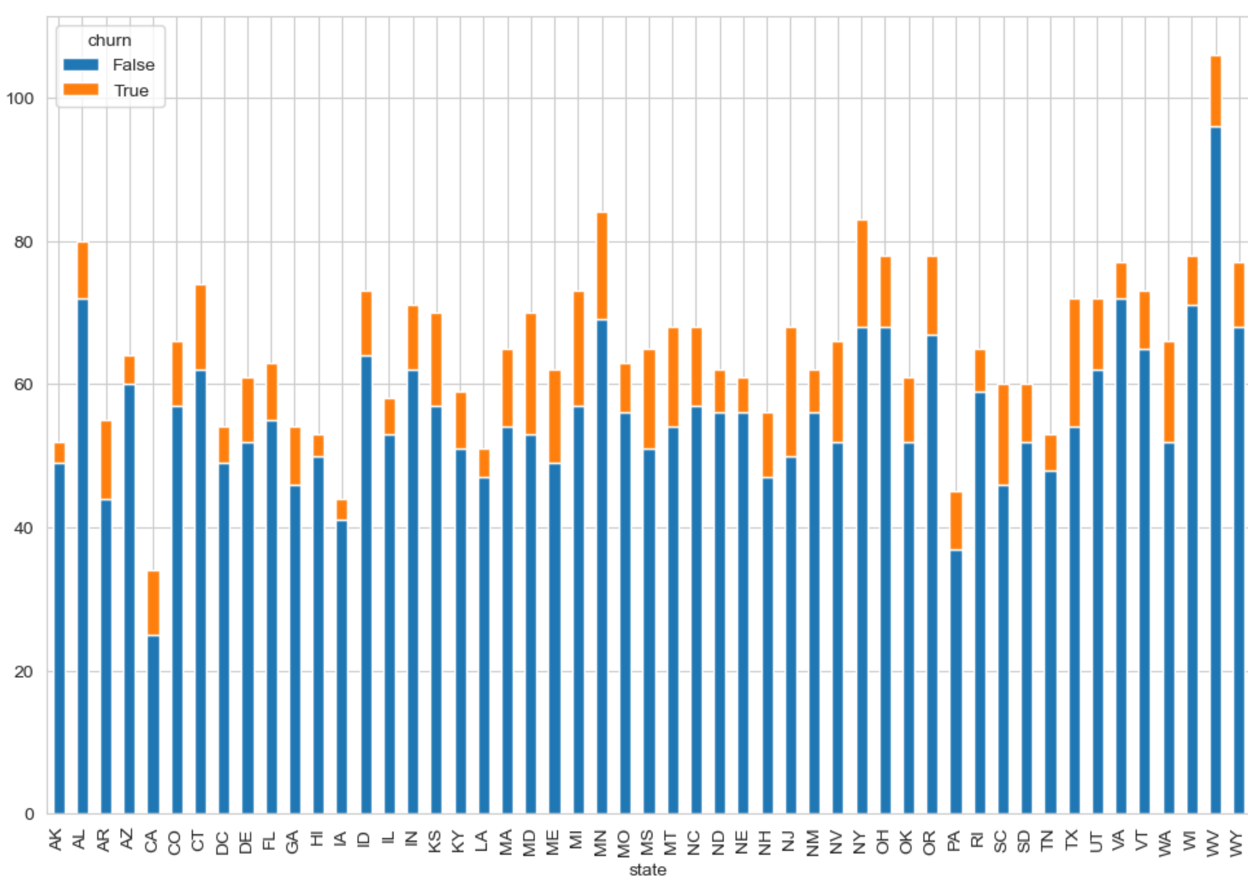
Out[16]: <Axes: xlabel='voice mail plan'>



From the category voice mail plan, a higher percentage are not subscribed to the plan. From those who are not subscribed, a smaller number churned. Of the voice plan subscribers, a smaller section churned.

In [17]:
```python
#Visualizing the distribution of churned and non-churned customers grouped by their location, ie the state.
df.groupby(["state", "churn"]).size().unstack().plot(kind='bar', stacked=True, figsize=(12,8))
```

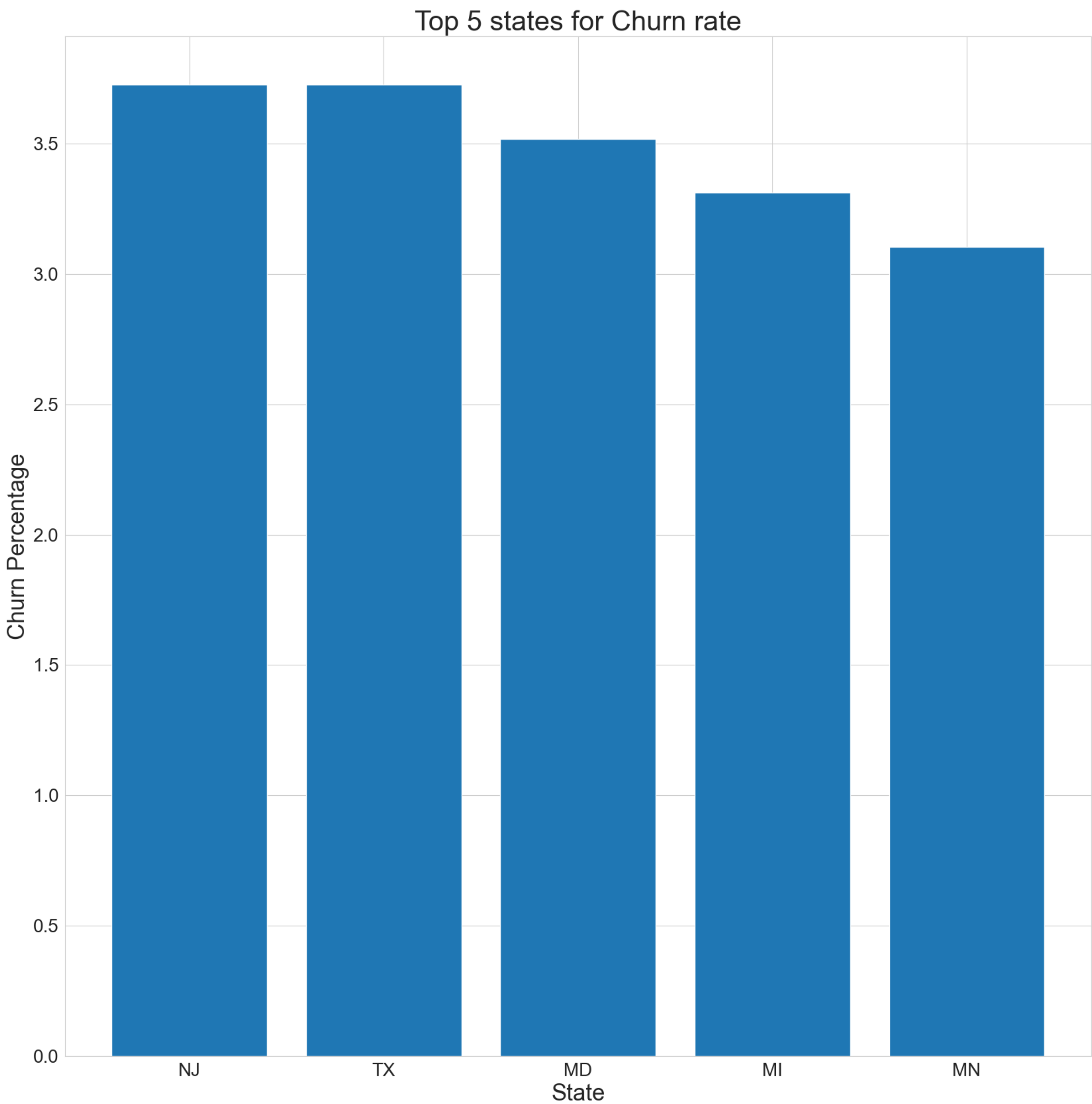
Out[17]: <Axes: xlabel='state'>



Generally in all the states, most people did not churn.

In [18]:

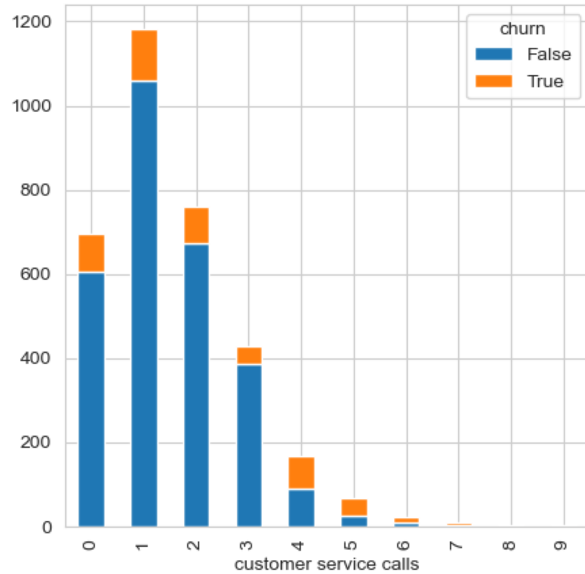
```
state_grouped = df.groupby(["state", "churn"]).size().unstack().reset_index()
sum_all_states = state_grouped[True].sum()
state_grouped['churn_percentage'] = (state_grouped[True] / sum_all_states) * 100
state_grouped.sort_values(by ='churn_percentage', ascending = False, inplace = True)
top_five_churn = state_grouped[:5]

fig, ax = plt.subplots(figsize=(20,20))
plt.bar(top_five_churn['state'], top_five_churn['churn_percentage'])
plt.title('Top 5 states for Churn rate', fontsize = 30)

ax.set_xlabel("State",fontsize=25)
ax.set_ylabel("Churn Percentage",fontsize=25)

plt.xticks(fontsize = 20)
plt.yticks(fontsize = 20)
sns.set_style('whitegrid')
```



Top 5 states with the highest churn rates are NJ, TX, MD, MI and MN

In [19]:
```
#Visualizing the distribution of churned and non-churned customers grouped by the customer service call they make.
df.groupby(["customer service calls", "churn"]).size().unstack().plot(kind='bar', stacked=True, figsize=(5,5))
```

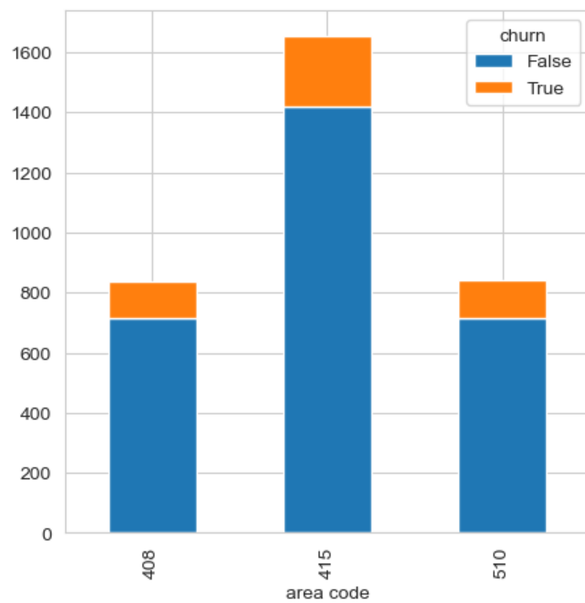
Out[19]: <Axes: xlabel='customer service calls'>



Most of the subscribers do make one customer service call. With subscribers having one customer service call churning the most.

In [20]:
```
#Visualizing the distribution of churned and non-churned customers grouped by their Area Code.
df.groupby(["area code", "churn"]).size().unstack().plot(kind='bar', stacked=True, figsize=(5,5))
```

Out[20]: <Axes: xlabel='area code'>



From the visualization above most of the subscribers did not churn. With area code 415 having a higher number of subscribers who churned.

Modeling

Data Transformation

In [21]:
```
# methods used: laber encoder
#Transforming categorical variables into numerical variables

label = LabelEncoder()

df['state'] = label.fit_transform(df['state'])
df['international plan'] = label.fit_transform(df['international plan'])
df['voice mail plan'] = label.fit_transform(df['voice mail plan'])
df['churn'] = label.fit_transform(df['churn'])

# Change the data types to int
df['state'] = df['state'].astype(int)
df['international plan'] = df['international plan'].astype(int)
df['voice mail plan'] = df['voice mail plan'].astype(int)
df['churn'] = df['churn'].astype(int)
```

In [22]:
```
# Selecting the Independent Variables (X) and Target Variable (y)
X = df.drop(columns=['state','churn','phone number'], axis=1)
y = df['churn']
```

In [23]:
```
# Spliting the dataset into training and testing sets using a 75-25 ratio,
#ensuring reproducibility with a fixed random state of 42

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25, random_state=42)
```

Logistic Regression

In [24]:
```
# Using Pipeline for machine learning.
# Using MinMaxScaler for feature Scalling
# Using Logistic Regression as our model

logistic_pipeline = Pipeline([('mms', MinMaxScaler()),
                              ('LR', LogisticRegression(fit_intercept=False, solver='liblinear', max_iter=12000, random_sta
```

In [25]:
```
# Fitting the logistic regression model to the train dataset
logistic_pipeline.fit(X_train, y_train)
```

Out[25]:
```
Pipeline
  MinMaxScaler
  LogisticRegression
```

In [26]:
```
# Checking for class imbalance.
y_train.value_counts()
```

Out[26]:
```
0    2141
1     358
Name: churn, dtype: int64
```

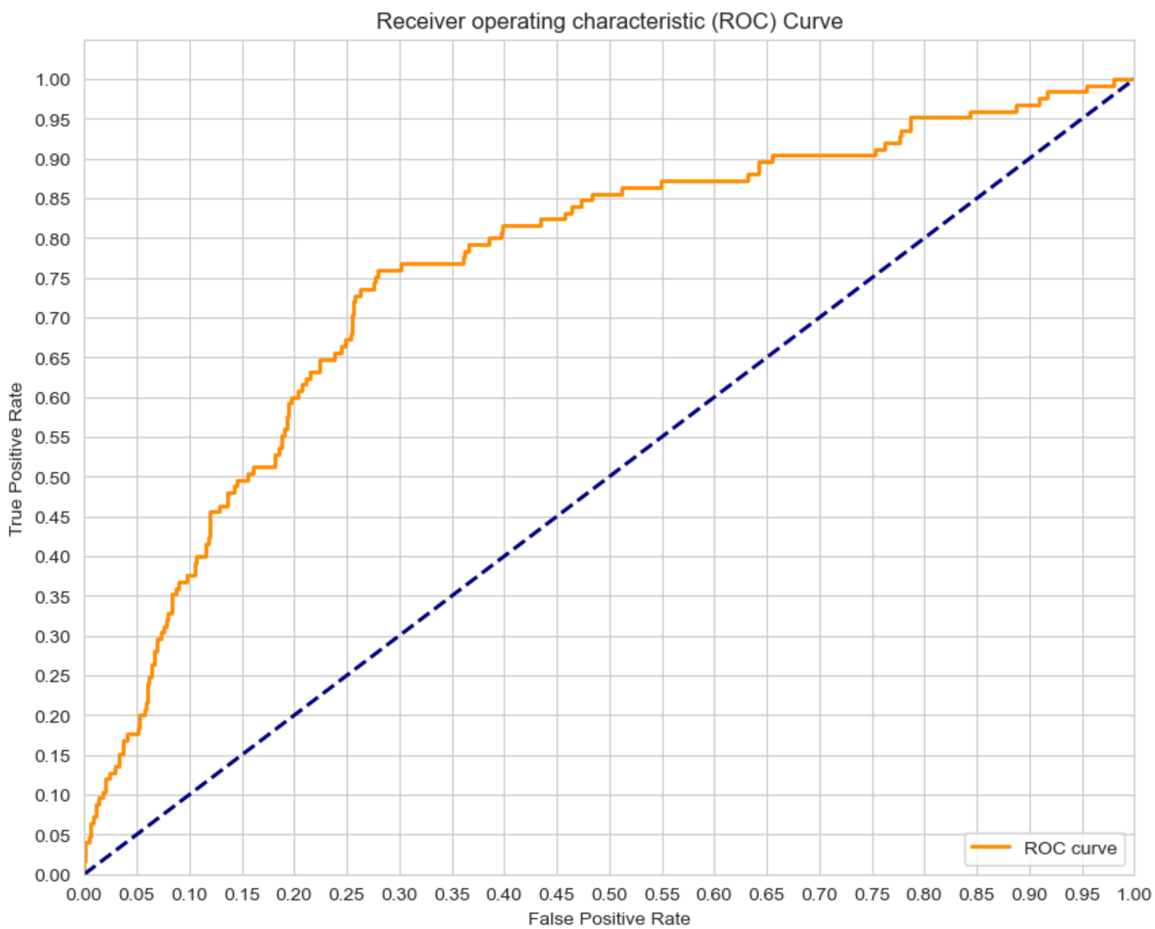
From the results above there is a class imbalance issue with majority of class being '0'
There is need to balance the classes to improve accuracy

In [27]:
```
# Evaluating the accuracy score for train and test data
accuracy_train=logistic_pipeline.score(X_train, y_train)
accuracy_test=logistic_pipeline.score(X_test, y_test)
print(f"Accuracy score for train: {accuracy_train}",
     "\n\n",f"Accuracy score for test: {accuracy_test}")
```

```
Accuracy score for train: 0.8623449379751901

 Accuracy score for test: 0.8501199040767387
```

In [28]:
```
# Plotting the AUC curve
y_score = logistic_pipeline.decision_function(X_test)
fpr, tpr, thresholds = roc_curve(y_test, y_score)
print('AUC', auc(fpr,tpr))

plt.figure(figsize=(10, 8))
lw = 2
plt.plot(fpr, tpr, color='darkorange',
         lw=lw, label='ROC curve')
plt.plot([0, 1], [0, 1], color='navy', lw=lw, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.yticks([i/20.0 for i in range(21)])
plt.xticks([i/20.0 for i in range(21)])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic (ROC) Curve')
plt.legend(loc='lower right')
plt.show()
```

```
AUC 0.7609139633286318
```



Improving the logistic model

In [29]:
```
# Using SMOTE to deal with class imbalance
#SMOTE contributes to more accurate predictions and better model performance
from imblearn.over_sampling import SMOTE

print('Original class distribution: \n')
print(y.value_counts())
smote = SMOTE(random_state=42)
X_train_resampled, y_train_resampled = smote.fit_resample(X_train, y_train)
# Preview synthetic sample class distribution
print('-----------------------------------------')
print('Synthetic sample class distribution: \n')
print(pd.Series(y_train_resampled).value_counts())
```

```
Original class distribution:

0    2850
1     483
Name: churn, dtype: int64
-----------------------------------------
Synthetic sample class distribution:

0    2141
1    2141
Name: churn, dtype: int64
```

In [30]:
```
#  Logistic Regression model using balanced classes
logistic_pipeline_resampled = Pipeline([('mms', MinMaxScaler()),
                                        ('LR', LogisticRegression(fit_intercept = False, solver = 'liblinear', max_iter = 1
```

In [31]:
```
# Fitting the model.
logistic_pipeline_resampled.fit(X_train_resampled, y_train_resampled)
```

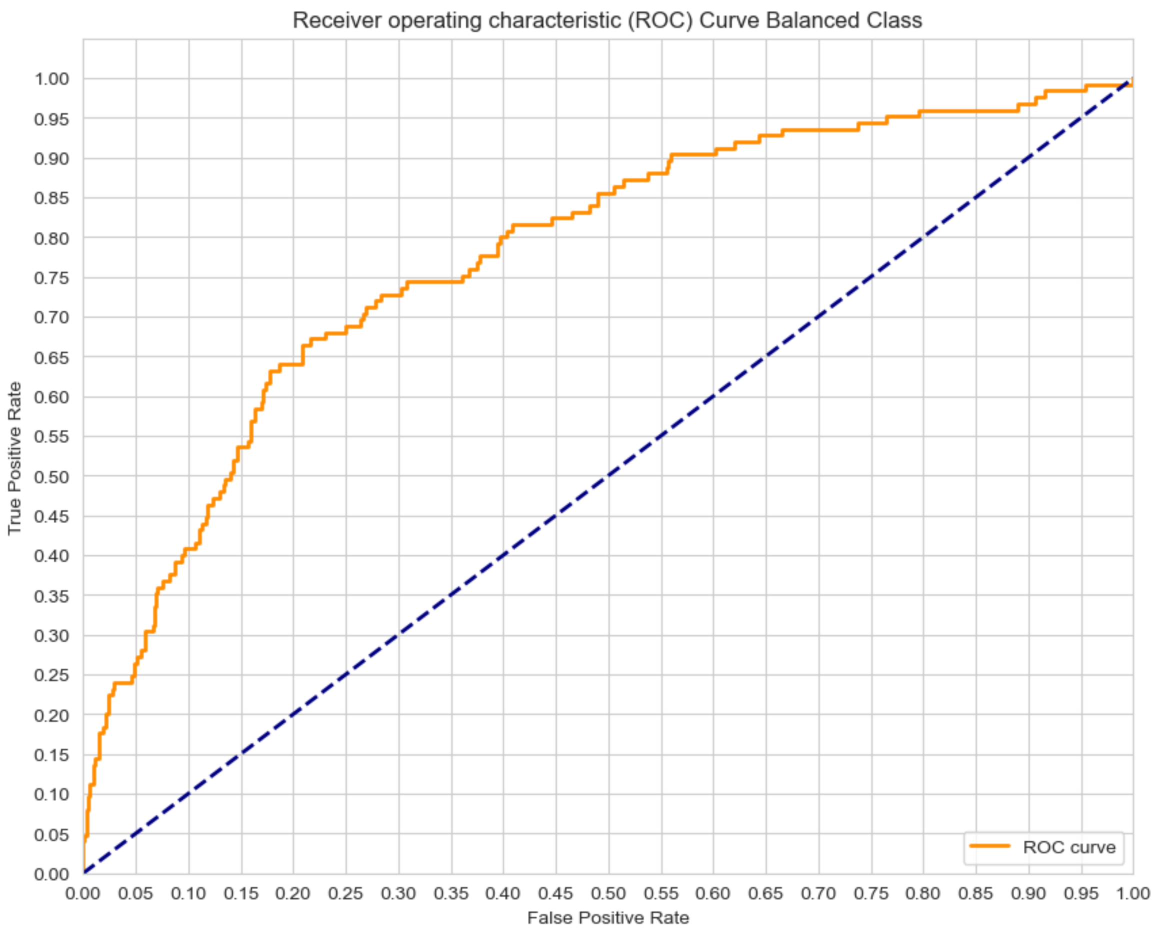
Out[31]:
```
Pipeline
  MinMaxScaler
  LogisticRegression
```

In [32]:
```
# Evaluating the accuracy score of the model on the testing data
accuracy_train_resampled=logistic_pipeline_resampled.score(X_train_resampled, y_train_resampled)
accuracy_test_resampled=logistic_pipeline_resampled.score(X_test, y_test)
print(f"Accuracy score for train: {accuracy_train_resampled}",
     "\n\n",f"Accuracy score for test: {accuracy_test_resampled}")
```

```
Accuracy score for train: 0.7274638019617001

 Accuracy score for test: 0.7122302158273381
```

In [33]:
```
# Computing for the AUC metric for model evaluation
y_score_resampled = logistic_pipeline_resampled.decision_function(X_test)
fpr, tpr, thresholds = roc_curve(y_test, y_score_resampled)
print('AUC_Balanced:', auc(fpr,tpr))

# Plotting AUC curve after dealing with class imbalance
plt.figure(figsize=(10, 8))
lw = 2
plt.plot(fpr, tpr, color='darkorange',
         lw=lw, label='ROC curve')
plt.plot([0, 1], [0, 1], color='navy', lw=lw, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.yticks([i/20.0 for i in range(21)])
plt.xticks([i/20.0 for i in range(21)])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic (ROC) Curve Balanced Class')
plt.legend(loc='lower right')
plt.show()
```

```
AUC_Balanced: 0.7772411847672778
```



Tuning model: Hyperparameterization

In [34]:
```
#using GridSearchCV to tune hyperparameters of the model,
#Aiming to find the optimal combination of hyperparameters to maximizes the model's performance.

logistic_grid = [{'LR__C':[0.1, 1, 50, 2000, 1e8, 1e15],
                  'LR__penalty': ['l1', 'l2'],
                  'LR__solver' : ['liblinear', 'saga']}]

logistic_gridsearch = GridSearchCV(logistic_pipeline_resampled, logistic_grid, cv=3)
```

In [35]:
```
# Fitting the model.
logistic_gridsearch.fit(X_train_resampled, y_train_resampled)
```

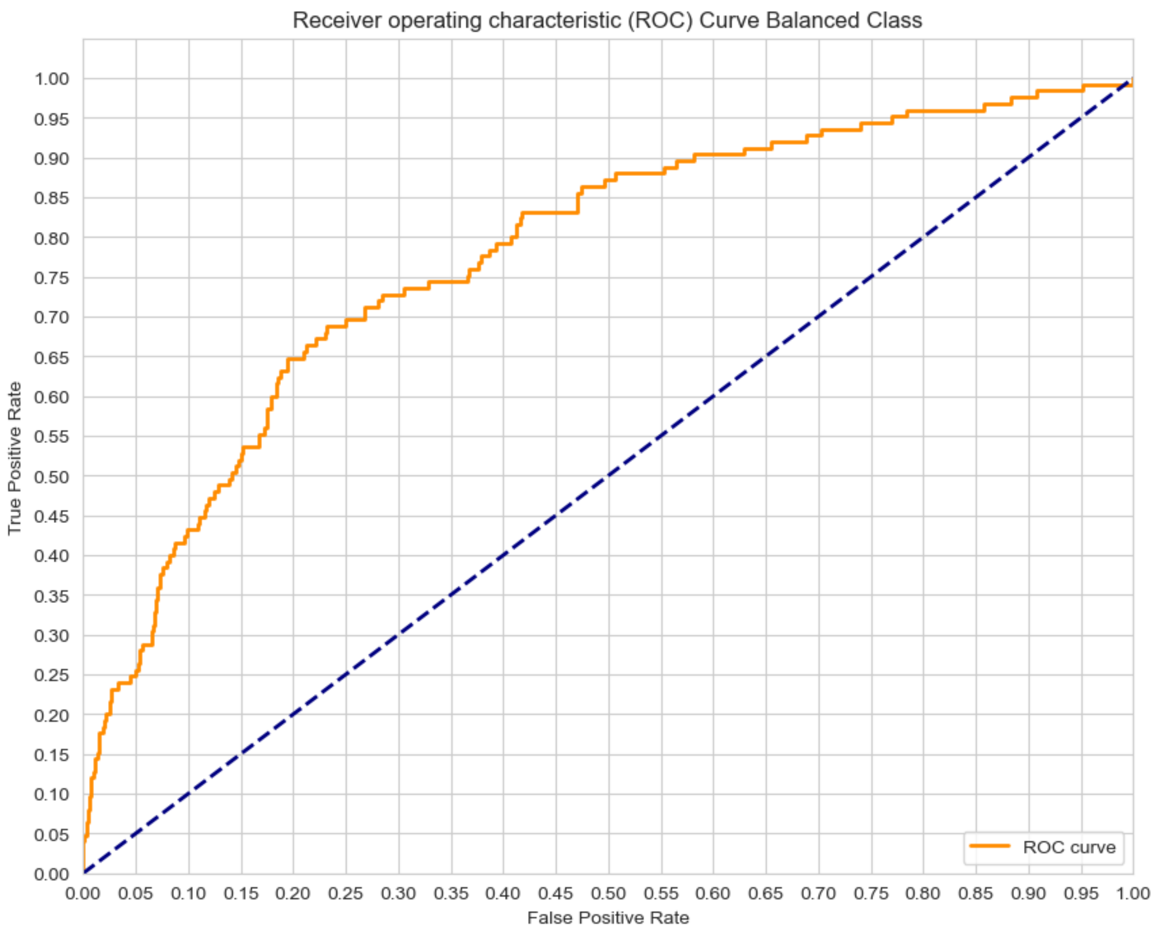
Out[35]:
```
▸ GridSearchCV
▸ estimator: Pipeline
  ▸ MinMaxScaler
  ▸ LogisticRegression
```

In [36]:
```
# Evaluating the accuracy score of the model
accuracy_train_grid=logistic_gridsearch.score(X_train_resampled, y_train_resampled)
accuracy_test_grid=logistic_gridsearch.score(X_test, y_test)
print(f"Accuracy score for train: {accuracy_train_grid}",
     "\n\n",f"Accuracy score for test: {accuracy_test_grid}")
```

```
Accuracy score for train: 0.7279308734236338

 Accuracy score for test: 0.7170263788968825
```

In [37]:
```
# Computing AUC
y_score_gridsearch = logistic_gridsearch.decision_function(X_test)
fpr, tpr, thresholds = roc_curve(y_test, y_score_gridsearch)
print('AUC_LR_Gridsearch:', auc(fpr,tpr))

# Displaying the ROC curve
plt.figure(figsize=(10, 8))
lw = 2
plt.plot(fpr, tpr, color='darkorange',
         lw=lw, label='ROC curve')
plt.plot([0, 1], [0, 1], color='navy', lw=lw, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.yticks([i/20.0 for i in range(21)])
plt.xticks([i/20.0 for i in range(21)])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic (ROC) Curve Balanced Class')
plt.legend(loc='lower right')
plt.show()
```

```
AUC_LR_Gridsearch: 0.7775232722143863
```



After parameter tuning, the training accuracy increased slightly from 0.7275 (72.75%) to 0.7279 (72.79%) while testing accuracy also increased slightly from 0.7122 (71.22%) to 0.7170 (71.70%) indicating an improvement in model performance.

The AUC increased slightly from 0.7772 to 0.7775 after parameter tuning, indicating an improvement in the model's ability to distinguish between positive and negative classe

However, further optimization using more advanced models may be needed for significant improvements.

Decision Tree

In [38]:
```
# building the Decision Tree model
DT_pipeline = Pipeline([('mms', MinMaxScaler()),
                        ('dt', DecisionTreeClassifier(random_state=42))])
```

In [39]:
```
#Fitting the model
DT_pipeline.fit(X_train_resampled, y_train_resampled)
```

Out[39]:
```
Pipeline
  MinMaxScaler
DecisionTreeClassifier
```

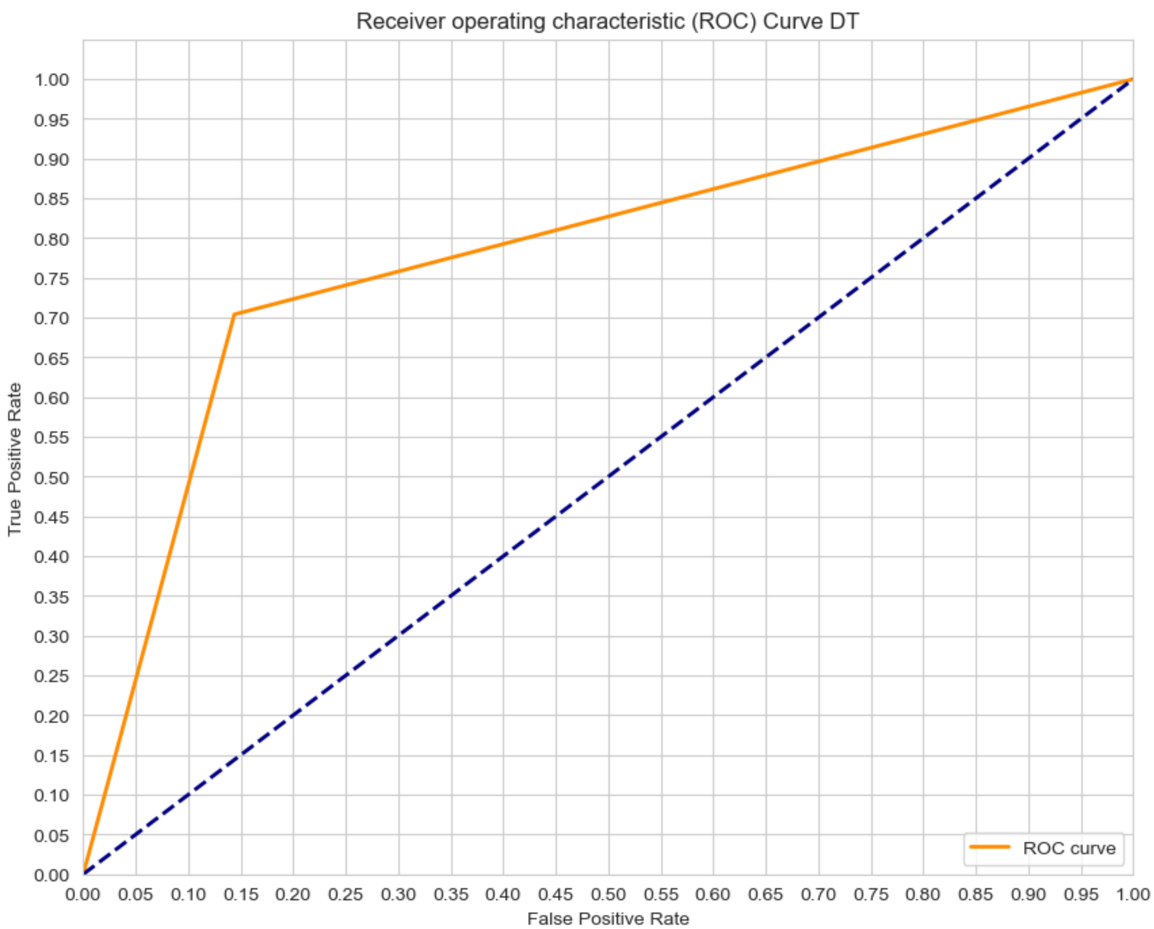
In [40]:
```
# Evaluating the accuracy score of the model on the testing data
train_score=DT_pipeline.score(X_train_resampled, y_train_resampled)
test_score= DT_pipeline.score(X_test, y_test)

print(f"Accuracy score for train: {train_score}",
     "\n\n",f"Accuracy score for test: {test_score}")
```

```
Accuracy score for train: 1.0

 Accuracy score for test: 0.8333333333333334
```

In [41]:

```
# Visualing the AUC curve
y_score_DT = DT_pipeline.predict_proba(X_test)[:,1]
fpr, tpr, thresholds = roc_curve(y_test, y_score_DT)
print('AUC_dt:', auc(fpr,tpr))

plt.figure(figsize=(10, 8))
lw = 2
plt.plot(fpr, tpr, color='darkorange',
         lw=lw, label='ROC curve')
plt.plot([0, 1], [0, 1], color='navy', lw=lw, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.yticks([i/20.0 for i in range(21)])
plt.xticks([i/20.0 for i in range(21)])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic (ROC) Curve DT')
plt.legend(loc='lower right')
plt.show()
```

```
AUC_dt: 0.780067700987306
```



Tuning to improve the model

In [42]:

```
#using GridSearchCV to tune hyperparameters our model,
#Aiming to find the optimal combination of hyperparameters that maximizes the model's performance.
DT_grid = {
    'dt__criterion': ['gini', 'entropy'],
    'dt__max_depth': [None, 2, 3, 4, 5, 6],
    'dt__min_samples_leaf': [1, 2, 3, 4, 5, 6],
    'dt__min_samples_split': [2, 5, 6, 10],
    'dt__random_state': [42]
}

# Perform Grid Search with cross-validation
Decision_Tree_gridsearch = GridSearchCV(DT_pipeline, DT_grid, cv=3)
```

In [43]:
```
#fit the model
Decision_Tree_gridsearch.fit(X_train_resampled, y_train_resampled)
```

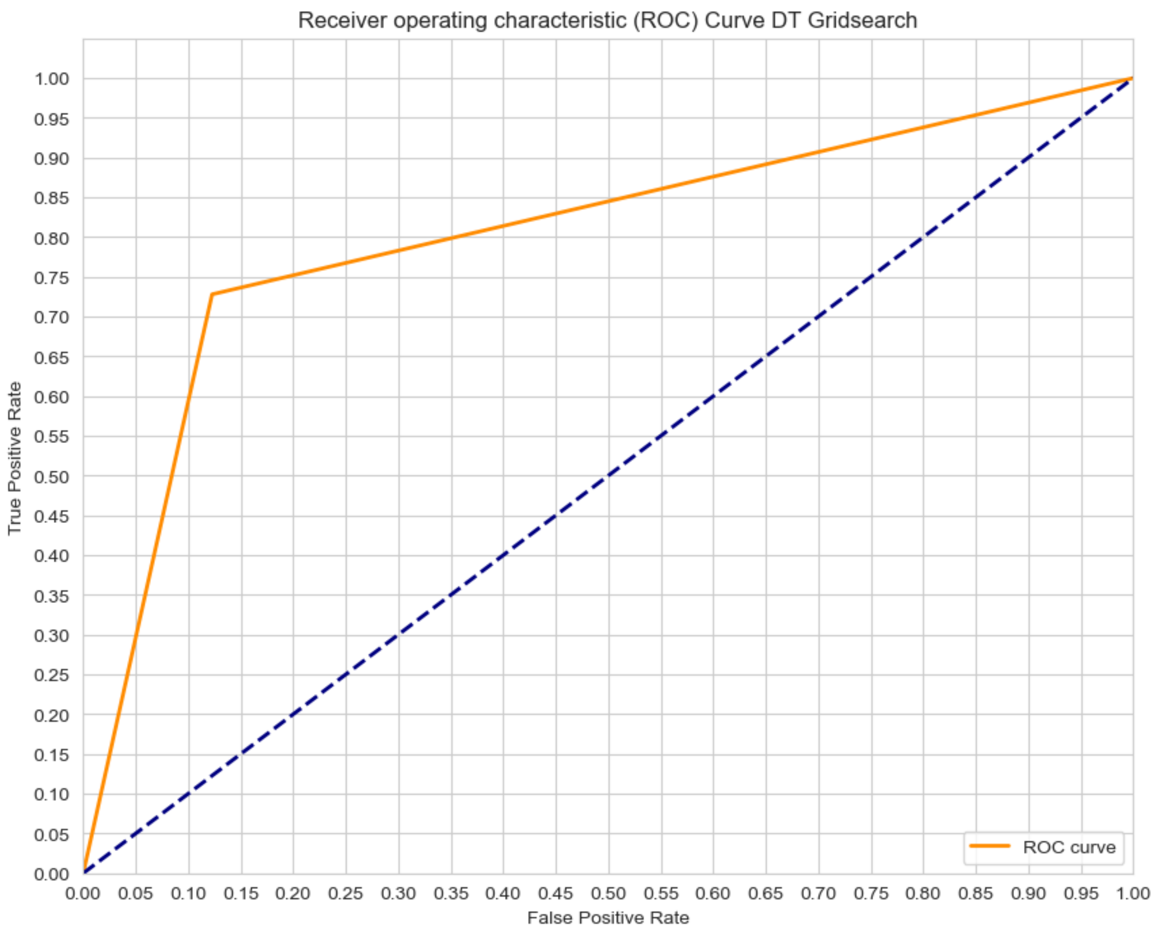
Out[43]:
```
▸ GridSearchCV
▸ estimator: Pipeline
  ▸ MinMaxScaler
  ▸ DecisionTreeClassifier
```

In [44]:
```
#evaluate model performance
train_score= Decision_Tree_gridsearch.score(X_train_resampled, y_train_resampled)
test_score=Decision_Tree_gridsearch.score(X_test, y_test)

print(f"Accuracy score for train: {train_score}",
     "\n\n",f"Accuracy score for test: {test_score}")
```

```
Accuracy score for train: 1.0

 Accuracy score for test: 0.854916067146283
```

In [45]:
```
y_score_dt_gridsearch = Decision_Tree_gridsearch.predict_proba(X_test)[:,1]
fpr, tpr, thresholds = roc_curve(y_test, y_score_dt_gridsearch)
print('AUC_dt_gridsearch:', auc(fpr,tpr))

plt.figure(figsize=(10, 8))
lw = 2
plt.plot(fpr, tpr, color='darkorange',
         lw=lw, label='ROC curve')
plt.plot([0, 1], [0, 1], color='navy', lw=lw, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.yticks([i/20.0 for i in range(21)])
plt.xticks([i/20.0 for i in range(21)])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic (ROC) Curve DT Gridsearch')
plt.legend(loc='lower right')
plt.show()
```

```
AUC_dt_gridsearch: 0.8026459802538787
```



The models exhibit signs of overfitting with perfect training accuracy (1.0) but lower testing accuracy, indicating memorization of the training data.

However, after parameter tuning, the testing accuracy improved from 0.8333 (83.33%) to 0.8549 (85.49%) suggesting improved generalization to unseen data hence improved model performance.

The AUC (Area Under the ROC Curve) increased from 0.7801 to 0.8026 after parameter tuning, indicating an improvement in the model's ability to distinguish between positive and negative classes.

Further optimization may be necessary to achieve optimal balance between model performance, generalization and to reduce overfitting by using a more advanced model like the Random Tree Classifier

In [46]:
```
def plot_feature_importances(model):
    n_features = X_train_resampled.shape[1]
    plt.figure(figsize=(8,8))
    plt.barh(range(n_features), model.feature_importances_, align='center')
    plt.yticks(np.arange(n_features), X_train_resampled.columns.values)
    plt.xlabel('Feature importance')
    plt.ylabel('Feature')
```

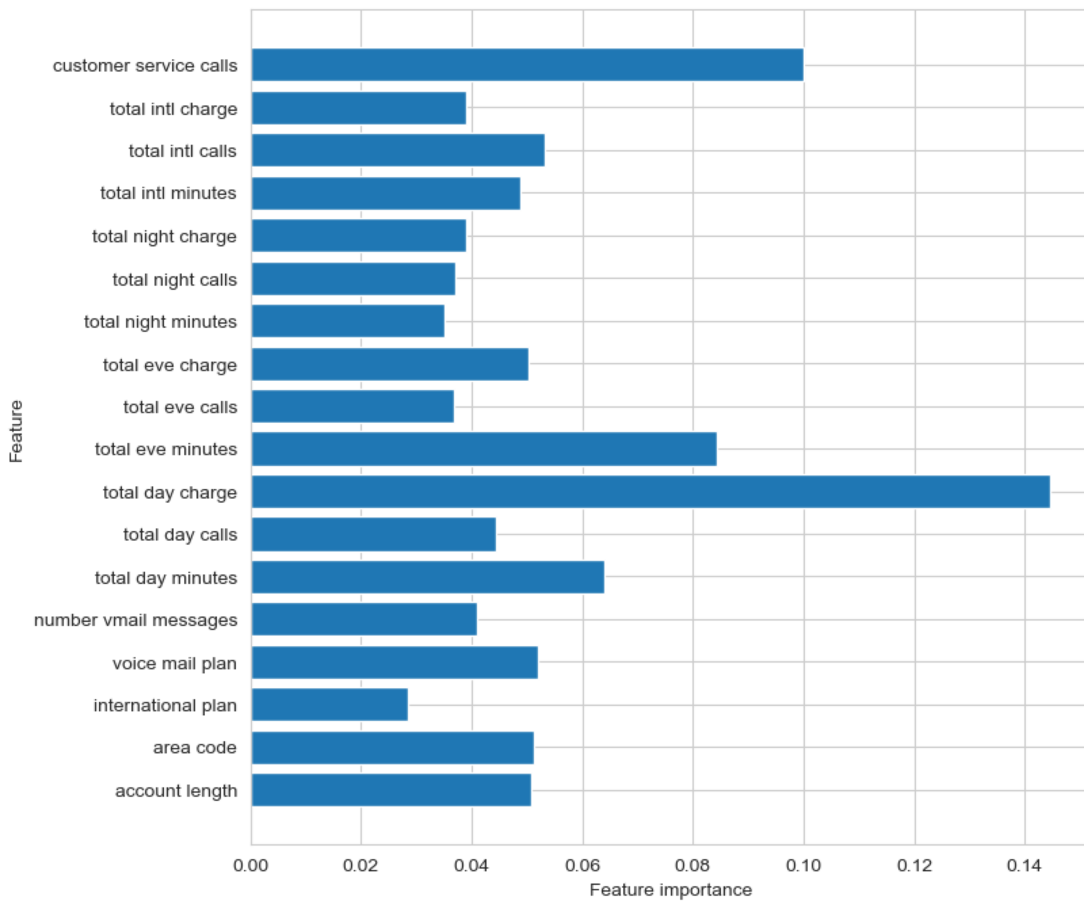
In [47]:
```
Decision_Tree_gridsearch.best_params_
```

Out[47]:
```
{'dt__criterion': 'entropy',
 'dt__max_depth': None,
 'dt__min_samples_leaf': 1,
 'dt__min_samples_split': 2,
 'dt__random_state': 42}
```

In [48]:
```
optimal_dt = DecisionTreeClassifier(criterion = 'entropy',
 max_depth = None,
 min_samples_leaf = 1,
 min_samples_split = 2,
 random_state = 42)
optimal_dt.fit(X_train_resampled, y_train_resampled)
```

Out[48]:
```
DecisionTreeClassifier
DecisionTreeClassifier(criterion='entropy', random_state=42)
```

In [49]:
```
plot_feature_importances(optimal_dt)
```



Customer service calls, total day charge and total eve minutes are the most important features in determining whether a customer will churn or not.

Random Forest Classifier

In [50]:
```
#Random Forest pipeline
rf_pipeline = Pipeline([('mms', MinMaxScaler()),
                        ('RF', RandomForestClassifier(random_state=42))])
```

In [51]:
```
#fit the training data
rf_pipeline.fit(X_train_resampled, y_train_resampled)
```

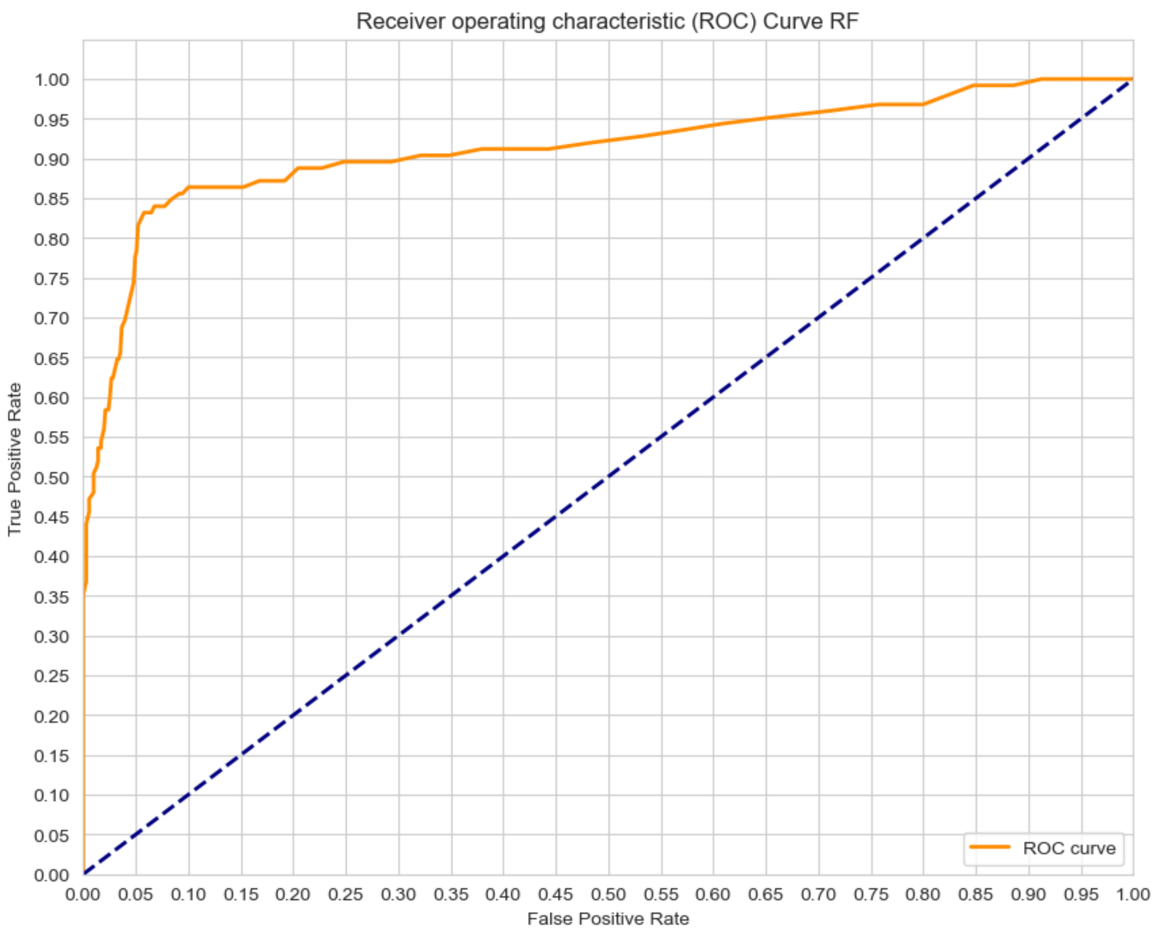
Out[51]:
```
Pipeline
  MinMaxScaler
  RandomForestClassifier
```

In [52]:
```
#evaluate model performance
train_score= rf_pipeline.score(X_train_resampled, y_train_resampled)
test_score=rf_pipeline.score(X_test, y_test)

print(f"Accuracy score for train: {train_score}",
     "\n\n",f"Accuracy score for test: {test_score}")
```

```
Accuracy score for train: 1.0

 Accuracy score for test: 0.920863309352518
```

In [53]:
```
#Visualizing the auc score
y_score_rf = rf_pipeline.predict_proba(X_test)[:,1]
fpr, tpr, thresholds = roc_curve(y_test, y_score_rf)
print('AUC_rf:', auc(fpr,tpr))

plt.figure(figsize=(10, 8))
lw = 2
plt.plot(fpr, tpr, color='darkorange',
         lw=lw, label='ROC curve')
plt.plot([0, 1], [0, 1], color='navy', lw=lw, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.yticks([i/20.0 for i in range(21)])
plt.xticks([i/20.0 for i in range(21)])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic (ROC) Curve RF')
plt.legend(loc='lower right')
plt.show()
```

```
AUC_rf: 0.9132581100141044
```



In [54]:
```
#Tuning the parameters of the model
rf_grid = {
    "RF__n_estimators": [10, 30, 100],
    "RF__criterion": ["gini", "entropy"],
    "RF__max_depth": [None, 2, 6, 10],
    "RF__min_samples_split": [5, 10],
    "RF__min_samples_leaf": [3, 6],
}

rf_gridsearch = GridSearchCV(rf_pipeline, rf_grid, cv=3)
```

In [55]:
```
#fitting the model
rf_gridsearch.fit(X_train_resampled, y_train_resampled)
```

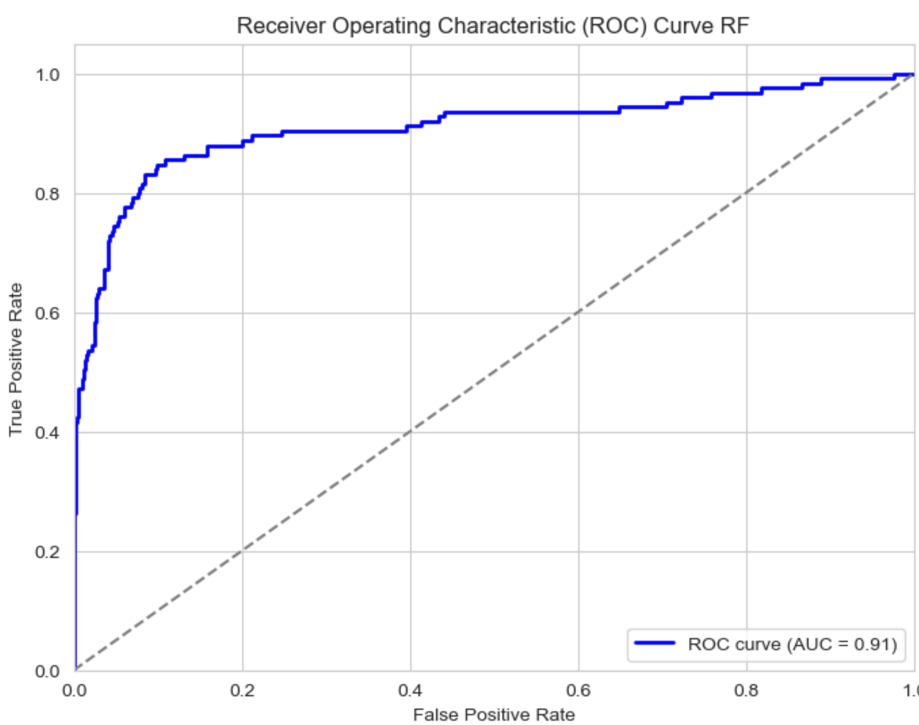
Out[55]:
```
GridSearchCV
estimator: Pipeline
MinMaxScaler
RandomForestClassifier
```

In [56]:
```
#evaluate model performance
train_score= rf_gridsearch.score(X_train_resampled, y_train_resampled)
test_score=rf_gridsearch.score(X_test, y_test)

print(f"Accuracy score for train: {train_score}",
     "\n\n",f"Accuracy score for test: {test_score}")
```

```
Accuracy score for train: 0.9915927136851939

 Accuracy score for test: 0.9220623501199041
```

In [57]:
```
#Calculating and visiualizing ROC
y_prob_rf_grid = rf_gridsearch.predict_proba(X_test)[:, 1]

# Compute ROC curve
fpr, tpr, thresholds = roc_curve(y_test, y_prob_rf_grid)

# Compute ROC AUC score
roc_auc_rf_grid = roc_auc_score(y_test, y_prob_rf_grid)
# Print ROC AUC score
print('AUC_rf_gridsearch:', roc_auc_rf_grid)


# Plot ROC curve
plt.figure(figsize=(8, 6))
plt.plot(fpr, tpr, color='blue', lw=2, label='ROC curve (AUC = %0.2f)' % roc_auc_rf_grid)
plt.plot([0, 1], [0, 1], color='gray', linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve RF')
plt.legend(loc='lower right')
plt.show()
```

```
AUC_rf_gridsearch: 0.9097658674188999
```



The model initially achieved perfect training accuracy (1.0), indicating potential overfitting, and a testing accuracy of 0.9209 (92.09%).

After parameter tuning, the training accuracy decreased slightly to 0.9916, suggesting a reduction in overfitting and increased generalization ability.

However, the testing accuracy increased to 0.9221 (92.21%) after parameter tuning indicating an improvement in the model's generalization performance on unseen data.

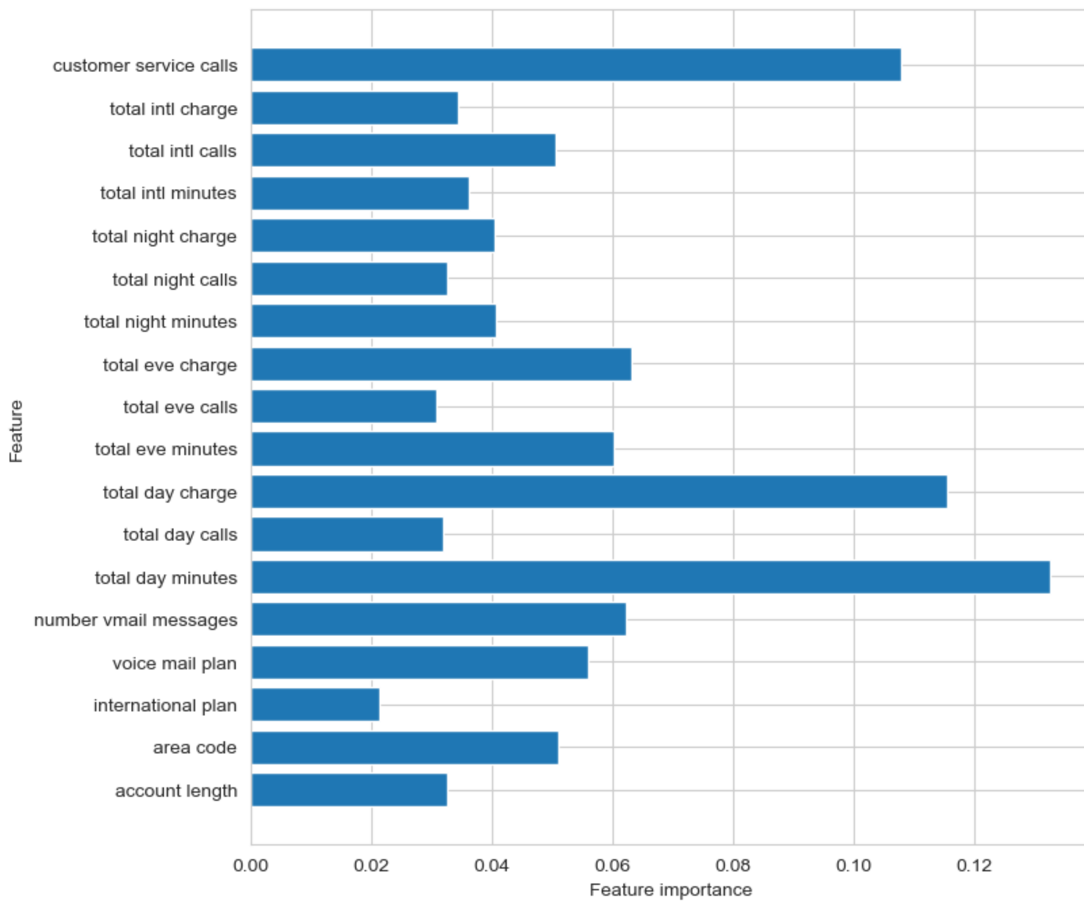
The AUC, however, decreased from 0.9133 to 0.9098 after parameter tuning indicating a slight deterioration in the model's ability to distinguish between positive and negative classes. This suggests that the tuning process may have negatively impacted the model's discriminatory power. Despite the decrease, the AUC is still high and indicates the model's effectiveness/ ability in distinguishing between positive and negative classes

Further optimization may be necessary to achieve optimal balance between model performance and generalization using a more advanced model like Gradient Boosting Classifier

In [58]:
```
#Obtain the best parameters from the grid
rf_gridsearch.best_params_
```

Out[58]:
```
{'RF__criterion': 'gini',
 'RF__max_depth': None,
 'RF__min_samples_leaf': 3,
 'RF__min_samples_split': 5,
 'RF__n_estimators': 100}
```

In [59]:
```
#Obtaining the optimal Random Forest Classifier
optimal_rf = RandomForestClassifier(criterion= 'gini',
 max_depth= None,
 min_samples_leaf =  3,
 min_samples_split = 5,
 n_estimators = 100)

#fitting the ptimal model
optimal_rf.fit(X_train_resampled, y_train_resampled)

plot_feature_importances(optimal_rf)
```



Customer service calls, total day charge, and total day minutes are the most important features in determining whether a customer will churn or not

Gradient Boosting Classifier

In [60]:
```python
## import Gradient Boosting Classifier
from sklearn.ensemble import GradientBoostingClassifier
```

In [61]:
```python
#create a model
gb_pipeline = Pipeline([('mms', MinMaxScaler()),
                        ('GB', GradientBoostingClassifier(random_state=42))])
```

In [62]:
```python
#fit the model
gb_pipeline.fit(X_train_resampled, y_train_resampled)
```

Out[62]:

```
Pipeline
MinMaxScaler
GradientBoostingClassifier
```

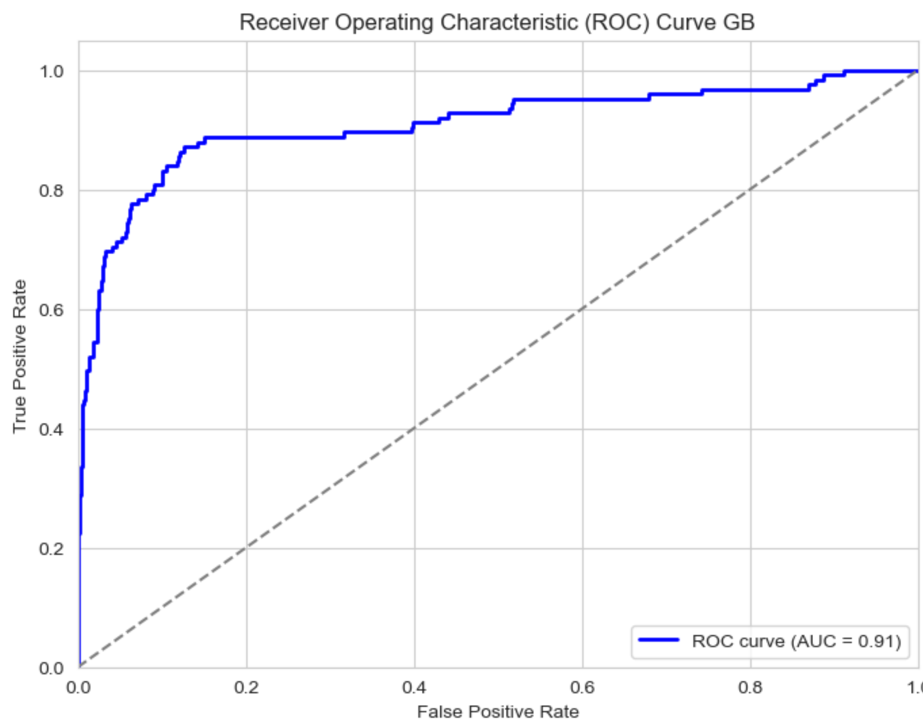
In [63]:
```python
#evaluate model performance
train_score= gb_pipeline.score(X_train_resampled, y_train_resampled)
test_score=gb_pipeline.score(X_test, y_test)

print(f"Accuracy score for train: {train_score}",
     "\n\n",f"Accuracy score for test: {test_score}")
```

```
Accuracy score for train: 0.9098552078468005

 Accuracy score for test: 0.9100719424460432
```

In [64]:

```
#Calculating and visiualizing ROC
y_prob_gb = gb_pipeline.predict_proba(X_test)[:, 1]

# Compute ROC curve
fpr, tpr, thresholds = roc_curve(y_test, y_prob_gb)

# Compute ROC AUC score
roc_auc_gb_pipeline = roc_auc_score(y_test, y_prob_gb)
# Print ROC AUC score
print('AUC_gb:', roc_auc_gb_pipeline)


# Plot ROC curve
plt.figure(figsize=(8, 6))
plt.plot(fpr, tpr, color='blue', lw=2, label='ROC curve (AUC = %0.2f)' % roc_auc_rf_grid)
plt.plot([0, 1], [0, 1], color='gray', linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve GB')
plt.legend(loc='lower right')
plt.show()
```

```
AUC_gb: 0.909179125528914
```



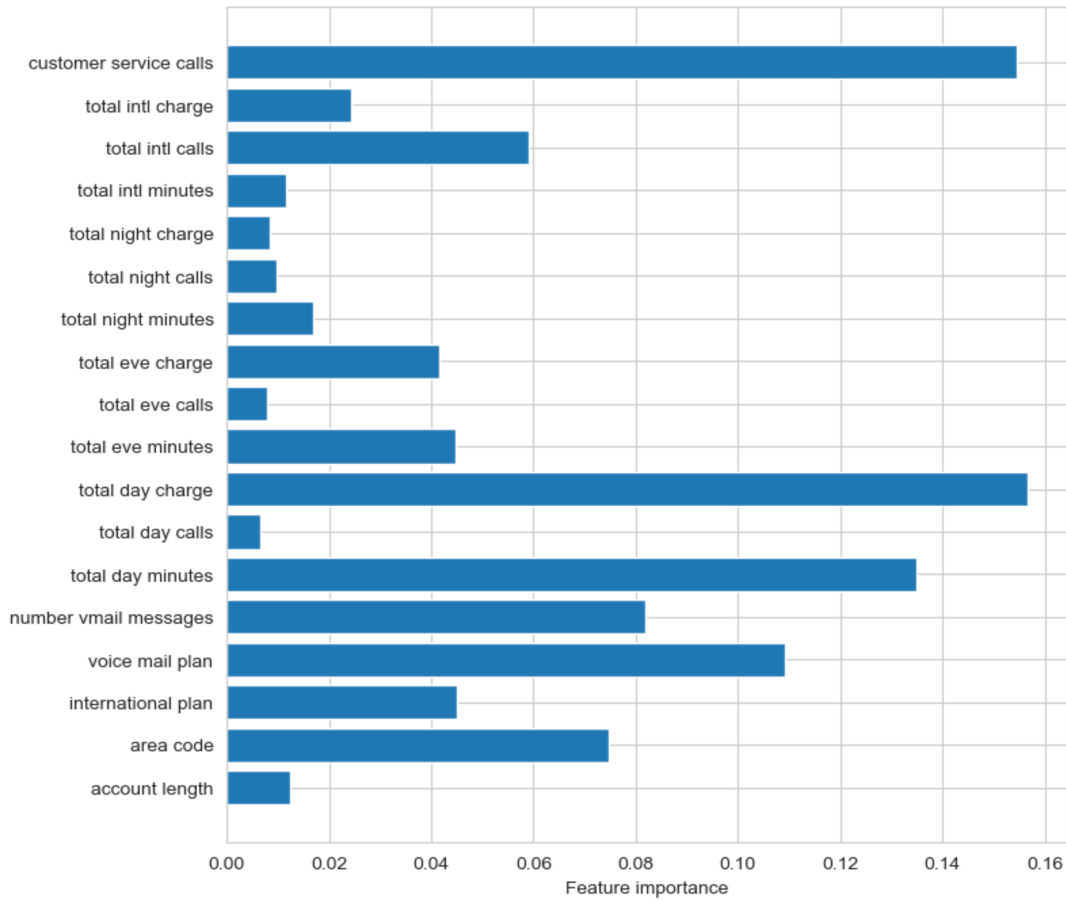
Both the training and testing accuracy scores are relatively high, with the training accuracy at 0.9166 and the testing accuracy at 0.9221. This indicates that the model performs well on both the data it was trained on and unseen data.

Despite a slightly lower AUC(90.92%) compared to Random Forest (90.98%), the model's performance is still impressive and indicates its effectiveness / ability to distinguish between positive and negative classes.

Nevertheless, the close proximity of the training and testing accuracies suggests that the model generalizes well to unseen data, without overfitting to the training set. Overall, these results indicate that the model is robust and performs well in classifying the data, demonstrating its effectiveness in making accurate predictions.

In [65]:

```
#Feature Importance-GB
def plot_feature_importances_gb(model):
    final_model = model.steps[-1][1]
    n_features = X_train_resampled.shape[1]
    plt.figure(figsize=(8,8))
    plt.barh(range(n_features), final_model.feature_importances_, align='center')
    plt.yticks(np.arange(n_features), X_train_resampled.columns.values)
    plt.xlabel('Feature importance')
    plt.show()

plot_feature_importances_gb(gb_pipeline)
```



Customer service calls, total day charge, total day minutes and voice mail plan are the most important features in determining whether a customer will churn or not.

Conclusion

After running the data through Logistic Regression, Decision Tree, Random Forest and Gradient Boosting Classifier and tuning the hyperparameters, the Gradient Boosting Classifier yielded the best results with a training accuracy at 0.9099(90.99%) and the testing accuracy at 0.9101(91.01%). This indicates that the model performs well on both the data it was trained on and unseen data.

Overall, the Gradient Boosting model demonstrates strong performance with high accuracy and AUC scores on both the training and testing sets, indicating its effectiveness in making accurate predictions.